An Integrated Approach to the Discrimination of Riparian Vegetation in the Navarro River Watershed, Mendocino County, California, USA

Joshua H. Viers, ¹ Charlene T. Sailer, ² Carlos M. Ramirez, ¹ James F. Quinn, ¹ AND Michael L. Johnson³

In July of 2000, the Information Center for the Environment (ICE) and Center for Spatial Technologies and Remote Sensing (CSTARS) collaborated with National Aeronautics and Space Administration – Jet Propulsion Laboratory (NASA – JPL) to obtain Airborne Visible InfraRed Imaging Spectrometer (AVIRIS) data of the Navarro River watershed. The Navarro River watershed is located in southern Mendocino County, California, USA. This watershed, 820 km² in size, drains into the Pacific Ocean and provides a unique opportunity to investigate a closed hydrologic system (Figure 1). A mixture of redwood and mixed conifer forests, oak woodlands, open grasslands, and agricultural areas provides an array of land uses from which to analyze interactions with aquatic and riparian habitats. The Navarro River watershed supports a resource-based economy; timbering, grazing, and limited cropping are the primary land use activities in the watershed. However, recent changes in the California economy have resulted in increased viticultural activities and an increase in the local human population (ca. 3500) within this watershed. These combined factors have resulted in pervasive land use change in the last 150 years, from which researchers have sought to inventory, catalogue, and provide a synopsis of the ecological state of the watershed.

Using a large area, high spatial resolution collection of AVIRIS data for the Navarro River watershed, a classification of riparian vegetation was initiated using a combination of traditional ecological assessment techniques and hyperspectral data analysis. The Navarro River watershed is the focal point of many ongoing, multidisciplinary investigations concerning anthropogenic disturbance of watershed processes, such as logging, road building, and land conversion to vineyards and other agriculture, and resulting ecological responses. Namely, these studies have focused on the role that land use activities play in perturbing anadromous salmonid populations and habitat. Riparian vegetation is a key habitat parameter in that it regulates many of the ecosystem components necessary for salmon reproduction, rearing, and migration through its effect on stream shading, contribution of large woody debris, and allocthonous inputs to the stream system, none which can be assessed comprehensively from ground studies due both to the size of the area and limited access to private lands. The primary goal of this project was to test the suitability of hyperspectral analytical techniques to identify and asses riparian vegetation over an area with complex topography and land use. In particular, our goals were to use ecological field data to 1) provide *a priori* expectations of vegetation classifications, 2) serve as a verification for spectral classification, and 3) to serve as a basis from which to nest the classification results within ongoing, national efforts of cataloging vegetation.

A series of traditional vegetation classification methods were employed on field data to determine the expected species composition of vegetation communities within the riparian zone. The traditional methods of vegetation classification from field collections are based on clustering algorithms and factor analyses, such as TWINSPAN (Hill, 1979), and these methods were used to establish an expected distribution of species for the watershed. To limit spectral feature extraction of possible riparian vegetation to locations near waterways, a riparian zone was delineated by using topographic features generated from a digital elevation model of the watershed. The process results in a hierarchical framework with expected species distributions that represent field conditions; this framework was then integrated with hyperspectral feature extraction methods, such as endmember selection, to discriminate different vegetation communities within the riparian zone.

Efforts to bridge vegetation community ecology and spectral technologies are not new; however, the use of hyperspectral data analysis to elucidate both specific constituents of vegetation communities and intra-community differences is a dynamic, adaptive science (Roberts et al., 1998). Techniques of both vegetation ecologists and spectrometrists are directed toward pattern detection. Vegetation ecologists typically do not test *a priori* hypotheses – studies are far more often observational or descriptive, with a focus on inductive, multivariate methodologies. Similarly, spectrometry relies on the multi-, or hyper-, variate differences among materials to effectively discriminate and identify classes of objects. In this paper, we engage in methods to identify physical relationships that are evident in both ecological and spectral space. Namely, riparian plant species were identified and categorized into communities on the ground. AVIRIS data were used to both classify vegetation communities within the riparian

¹ Department of Environmental Science and Policy, University of California, Davis (jhviers@ucdavis.edu)

² Crocker Nuclear Laboratory, University of California, Davis

³ John Muir Institute of the Environment, University of California, Davis

zone and to identify diagnostic species spectrally. The results of our study indicate that the composition of species within vegetation communities is reflected in both variable spaces: ecological and spectral.

Methods:

The following software packages were necessary for the procedures detailed below: ESRI ArcInfo v. 8.0.2 (Environmental Systems Research Institute, Inc.); ERDAS Imagine v. 8.5(Leica Geosystems, Atlanta, Georgia); RSI ENVI v. 3.5 (Research Systems Inc., Boulder, Colorado); RSI IDL v. 5.5 (Research Systems Inc., Boulder, Colorado); PARGE v. 1.3 and ATCOR4 v. 2.0 (ReSe Application Schläpfer, Zurich, Switzerland), and PC ORD v. 4.14 (MjM Software, Gleneden, Oregon).

In all, NASA flew 26 of the 29 proposed flightlines over a period of three days in late July of 2000. For this preliminary hybrid classification analysis, we have chosen one representative flightline (FL) from the collection to process: FL 18 (Figure 1). Elevation of the study site ranges from sea level to 1054 m with most ridge tops paralleling the San Andreas Fault in a southeast to northwest direction toward the Pacific Ocean.

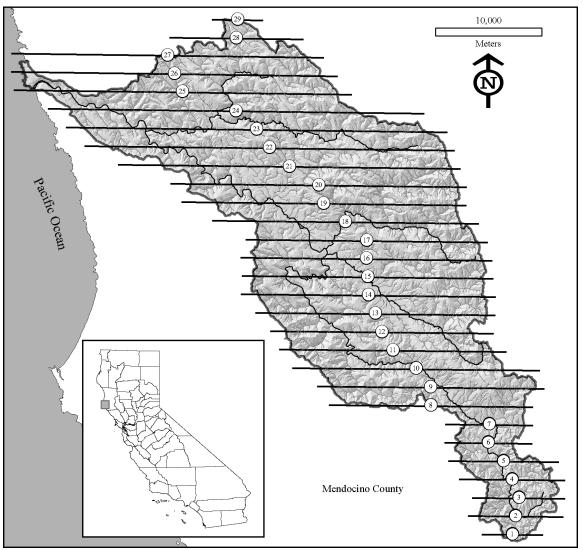


Figure 1. Map of the Navarro River watershed with the proposed AVIRIS flightlines and primary hydrographic features. All but flightlines 1-3 were flown in July 2000. Flightline 18 is the focus of this study. Inset Map shows position of watershed in Mendocino County, California.

NASA – JPL supplied the AVIRIS data in radiometrically corrected format on 8mm tape. Tape contents were uncompressed to a common file space on a sixteen-processor SGI Origin 2000 supercomputer; each flightline

totals approximately 1.5 - 2.5 gigabytes. To geometrically correct flightline data, a terrain correction software package, Parametric Geocoding (PARGE) (Schläpfer, 2000), was used. PARGE integrates the inertial navigation unit readings, flight GPS positions, and ground control points (GCPs) to correct for pitch, roll, heading, and yaw. This procedure also incorporates a Digital Elevation Model to adjust for topographic effects. Prior to initiating PARGE, each frame was mosaicked in ENVI to create a seamless flightline. AVIRIS data were converted from BIP to BSQ in ENVI. GCPs were collected by using a combination of ENVI and Imagine tool sets and Digital Orthophoto Quarter Quadrangles as a visual anchor. GCPs were systematically eliminated based on their X and Y coordinate offsets until the GCP Residual (RMSE) was less than 5.0 m. A 10-m USGS Digital Elevation Model of the watershed was resampled to 5 m cell resolution using bilinear interpolation and converted in ArcInfo from a grid to a DEM in USGS format (ESRI, 2001). The USGS format DEM was imported into ENVI to be used with PARGE, along with the GCPs. The final AVIRIS data were resampled to 5m from the native 3.3-m to 4.2-m spatial resolution. The geo-corrected results from PARGE, in addition to field spectra of pseudo-invariant targets, such as Navarro Beach and the Boonville Airport, were incorporated into ATCOR4, an atmospheric correction software package (Richter, 2000). ATCOR4 corrects for sun angle, atmospheric moisture and particulates, topography, offnadir viewing angles, and shadows. Once the FLs were geometrically and atmospherically corrected, "noisy" bands were eliminated. Bands were visually inspected and dropped from the analysis if their respective response signatures for a known material deviated from the expected response. The following bands were chosen as acceptable for further analysis: 2-104, 116-152, 168-220 (384.46 nm-1324.15 nm, 1443.7 9 nm-1802.45 nm, 1950.66 nm-2469.24 nm, respectively) and resulted in a final spectral product.

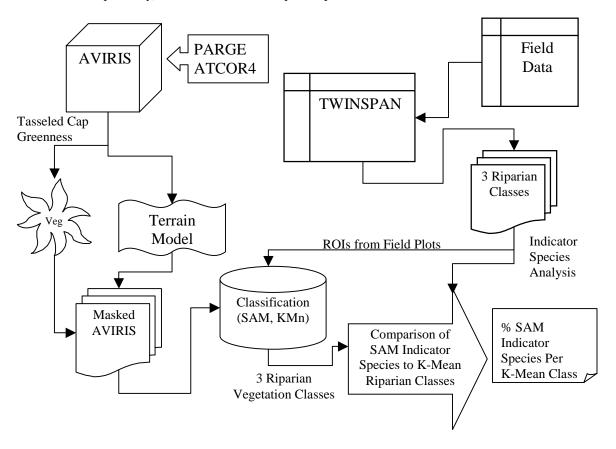


Figure 2. Processing flow diagram for the hybrid methodology to discriminate riparian vegetation.

The process for isolating riparian vegetation relies on a hybrid methodology, which incorporates an intersection of two masks, an ecological field data classification, a field-integrated spectral classification, an ecological field data indicator species analysis, and a final spectral comparison of indicator species within classes (Figure 2). The dual masking procedure is part terrain analysis and part spectral transformation. The spectral masking involved the transformation of the spectral array into three data planes using the Tasseled Cap transformation (Jackson, 1983, Richards and Jia, 1999). A processing script was developed in Interactive Data

Language (IDL) to extract data planes via the Tasseled Cap procedure for soil brightness, vegetation greenness, and water saturation (Jackson, 1983, Richards and Jia, 1999). The IDL script uses Regions of Interest (ROIs) as inputs for each data plane and the spectral downselected bands are used in the input array. To develop a series of ROIs, FL 18 was transformed using Boardman and Kruse's (1994) Minimum Noise Fraction (MNF) routine to collapse the input data array into 92 dimensions; ultimately the twenty dimensions with the highest eigenvalues were used for classification. ROIs were defined for pixels encoded by the Pure Pixel Index (1000 iterations) (Boardman et al., 1995) on the MNF transformed arrays. ROIs, in this case, were selected to represent soil brightness, vegetation greenness, and water saturation. Flightline 18 was examined for the distribution of values from the three-band transform array and each plane was bisected to separate materials based on its modal distribution. Vegetation was determined to have a "greenness" array value greater than the least first standard deviation from the mean.

To reduce spectral variability and errant classification of riparian vegetation in upland vegetation communities, the vegetation pixels were further segmented with a Riparian Extent Mask. The Riparian Extent data grid was created as a combination of two inputs. The first input is a Euclidean distance from streams data grid that was natural log transformed and rescaled from 1–100. A break point of 37.4 was chosen; it represents one standard deviation less than the mean. The second input represents the least cost path away from streams where Degree Slope is the cost. The results were natural log transformed and rescaled 1–100. A break point of 76.6 was chosen; it represents one standard deviation less than the mean. The Riparian Extent Mask represents the intersection of these two grids. This Riparian Extent Mask was then used to limit the influence of upslope vegetation on the spectral classification of the AVIRIS data and the Tasseled Cap Greenness plane was used as a mask to restrict the spectral classification to vegetation solely.

The hyperspectral classification incorporated the results of ecological data analysis of fieldwork conducted in the summer of 2000. The riparian fieldwork consisted of 6–10 m x 10 m quadrats randomly placed along each study reach at sixteen study sites throughout the watershed (Figure 3). Study sites were stratified to represent major tributaries in the watershed and position in the watershed, in terms of upstream accumulative drainage area. This stratification also recognizes differences in elevation, geologic substrates, and distance to the Pacific Ocean—a primary climatological determinate. We identified all woody species, estimated percent cover of each woody species, measured all stems greater than 10cm at diameter breast height, measured tree heights with a LaserTech Impulse 2000 Rangefinder, and located quadrat boundaries with a Trimble ProXRS DGPS. Additional field verification plots and individual species locations were geographically located with DGPS as well.

The species cover data were analyzed using Two-Way Indicator Species Analysis (Hill, 1979, McCune and Mefford, 1999). TWINSPAN can be described as dichotomized ordination analysis, in that an iterative character weighting is used to separate species affinities based on the incorporation of *pseudo-species* to represent differences in abundance for each observed species (van Tongeren, 1995). Similarly, sample sites are dichotomized and, ultimately, added to a species-by-site matrix. The result of this ordination is a fidelity matrix with an approximate positive diagonal, from upper-left to lower-right, which can be used to characterize un-sampled sites (van Tongeren, 1995); in this exercise, it is used as an *a priori* guide to vegetation communities within the riparian zone and resulted in three broad classes (Appendix I). Lastly, in terms of the ecological field data analysis, an Indicator Species Analysis was performed using the three Riparian Vegetation classes derived from TWINSPAN (Dufrene and Legendre, 1997). Indicator Species Analysis is a method that combines information on the concentration of species abundance for a particular group and the faithfulness of occurrence of a species in that group, as a function of frequency (McCune and Mefford, 1999). It produces indicator values for each species in each group, reflecting abundance and frequency, and this score is tested for statistical significance using a Monte Carlo technique (McCune and Mefford, 1999).

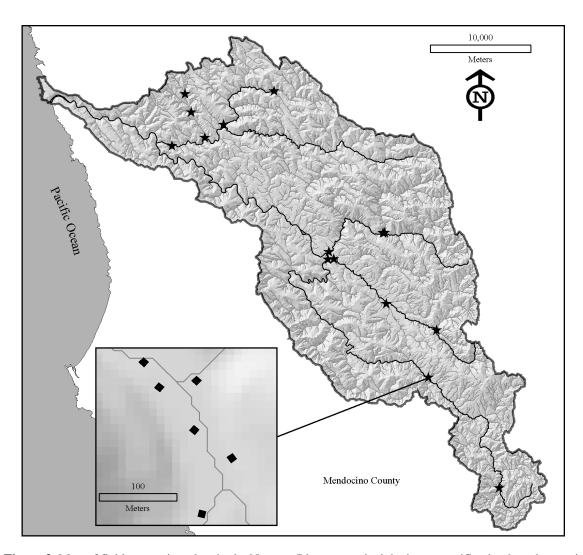


Figure 3. Map of field vegetation plots in the Navarro River watershed depicts a stratification based on major tributaries and watershed position. Study plots are 10 m x 10 m and are in clusters of six plots per site, as shown in the inset map.

Two classification methods were performed on the AVIRIS data to accomplish two separate, but related, objectives: 1) an unsupervised classification to establish vegetation communities within the riparian extent; and 2) a supervised classification of Indicator Species reference spectra to establish distributions of plant species indicative of vegetation communities. The purpose of this two-staged approach is to determine if hyperspectral data analysis can be used to identify patterns of species indicative of vegetation communities observed in the field; essentially, this two-stage method tries to establish whether vegetation communities observed in the field, in terms of composition and constancy, are reflected in the spectral characteristics of AVIRIS. A Spectral Angle Mapper (SAM) supervised classification was performed in ENVI using ROIs defined by the field quadrat boundaries and ancillary field identifications. The SAM classification (Kruse et al., 1993) was seeded to represent Indicator Species from the TWINSPAN classification using ROI endmembers for coast redwood, California bay laurel, and arroyo willow with a 0.1 radian deviance threshold from the reference spectra for classification. For each diagnostic species, a series of ROIs were identified, mean and standard deviation spectra were collected, and spectral libraries created to be used in the SAM classification. Additionally, a K-Means unsupervised classification was implemented on the twenty-band MNF in ENVI to classify vegetation communities within the riparian extent (Figure 4.1). A total of four classes were chosen to represent vegetation within the riparian extent (Figure 4.2); three classes are described in field plot results, and one class represents cultivated crops. The K-Means classification was performed with five hundred iterations and a 2% class deviance. Field plots and individual species' locations were geographically located with a Trimble ProXRS GPS unit, differentially corrected, and brought into ENVI as vector data for verification.

Results:

Using minimum criteria for TWINSPAN classification of field data, three broad classes of vegetation emerged. Two classes are typically considered upland vegetation; however, they are well represented in the riparian zone (Class A & B). These two classes have three species that are ubiquitous and representative: California bay laurel (*Umbellularia californica*), Douglas-fir (*Pseudotsuga menziesii*), and tanoak (*Lithocarpus densiflorus*). These two classes are separated by two diagnostic species: coast redwood (*Sequoia sempervirens*), and big-leaf maple (*Acer macrophyllum*); representing wetter and drier climes respectively. Other species that are marginally diagnostic are Pacific madrone (*Arbutus menziesii*) for wetter environments and coast live oak (*Quercus agrifolia*) for drier environments. The riparian class (Class C) is represented by a heterogeneous mixture of species; however, arroyo willow (*Salix lasiolepis*), Himalayan blackberry (*Rubus discolor*), and white alder (*Alnus rhombifolia*) emerged as diagnostic species. Other indicator species in this riparian class are: California blackberry (*Rubus vitifolius*), Pacific dogwood (*Cornus nuttallii*), and white willow (*Salix alba*). Furthermore, many of these species have significant Indicator Values in determining riparian class as determined by Indicator Species Analysis (Table 1), which determines a species Indicator Value as a function of abundance and frequency (Dufrene and Legendre, 1997). For Class A, redwood had the highest Indicator Value For Class B, California bay laurel was the best indicator species. Arroyo willow had the highest Indicator Value for Class C.

The results of the K-Means classification of the MNF transformed flightline 18 showed an overall accuracy of 71.77% and a Kappa Coefficient of 0.58 when using post-classification verification field plots. Class A (*Sequoia*) had a Producer's / User's Accuracy of 66.7% / 86.5%. Class B (*Umbellularia*) had a Producer's / User's Accuracy of 71.1% / 63.4%. Class C (*Salix*) had a Producer's / User's Accuracy of 78.9% / 72.3%. The results of the Spectral Angle Mapper classification for the three class diagnostic species (Table 1, in bold), determined from Indicator Species Analysis (results in Table 2), describe the relationship between vegetation community class, as defined by K-Means, and spectral libraries developed from field observation ROIs. The comparison of the SAM Indicator Species classification to the K-Means Community classification had overall accuracy 97.82% of and a Kappa Coefficient of 0.7471. These results are further detailed in Table 1.

Table 1. Results of Spectral Angle Mapper Classification on Discriminated Riparian Vegetation using field
mean and standard deviation spectra for selected Indicator Species defined by K-Means Classification.

<u>Class</u>	<u>Indicator Species</u>	No. SAM Pixels	No. Class Pixels	Pct. Indication by SAM
A	Sequoia sempervirens	46551	65822	70.72
В	Sequoia sempervirens	17745	46766	37.94
C	Sequoia sempervirens	4849	38890	12.47
A	Umbellularia californica	531	65822	0.81
В	Umbellularia californica	13486	46766	28.84
C	Umbellularia californica	1801	38890	4.63
A	Salix lasiolepis	15589	65822	23.68
В	Salix lasiolepis	13892	46766	29.71
C	Salix lasiolepis	20777	38890	53.43

Discussion:

Riparian vegetation communities identified in the field were identified spectrally via a restricted K-Means classification on MNF transformed AVIRIS data. The results of this classification, with an overall accuracy of 71.77%, suggest that the three vegetation classes within the riparian extent largely represent field observations (Figure 4.3) and the association with the field plots, classified by TWINSPAN to cluster communities of plant species, was generally correct. Thus, each spectral class had a representative surrogate field class that was verified via cluster analysis of field data plots. Additionally, and perhaps more significantly, SAM classification of AVIRIS data for selected species shows similar patterns of species associations observed in the field. In particular, Indicator Species Analysis, a method using species' observed abundance and frequency in relation to developed classes or communities, produced three diagnostic species for the three observed riparian communities. Spectral libraries of these diagnostic species were used in the SAM classification, which in turn were compared to the K-Means classified riparian communities. The overall accuracy of this comparison was 97.82%. Ultimately, these results indicate that the cross-comparison of individual species to classes was accurate in both field and spectral settings.

Table 2. Indicator Species Analysis Values and Probabilites for Sampled Riparian Plant Species in the Navarro River Watershed by Spectral Class.

111101	watershed by Spectral Class.				
	Taxon Name	Common Name	Class	Indicator Value	<u>p*</u>
1	Salix lasiolepis	arroyo willow	C	53.7	0.001
2	Acer macrophyllum	big-leaf maple	В	30.7	0.015
3	Umbellularia californica	California bay	В	68.1	0.001
4	Quercus kelloggii	California black oak	В	13.2	0.069
5	Rubus ursinus	California blackberry	C	20.8	0.121
6	Aesculus californica	California buckeye	В	2.4	1
7	Rhamnus californica	California coffeeberry	A	10.8	0.109
8	Corylus cornuta var. californica	California hazelnut	A	11.9	0.225
9	Torreya californica	California nutmeg	В	7.1	0.481
10	Vitis californica	California wild grape	В	7.3	0.415
11	Quercus chrysolepis	canyon live oak	В	10.5	0.159
12	Quercus agrifolia	coast live oak	В	17	0.069
13	Sequoia sempervirens	coast redwood	A	83.4	0.001
14	Ceanothus incanus	coast whitethorn	В	7.9	0.189
15	Salix hookeriana	coastal willow	C	6.6	0.327
16	Arctostaphylos manzanita	Common manzanita	В	2.6	1
17	Baccharis pilularis	coyote brush	C	14.3	0.023
18	Pseudotsuga menziesii var. menziesii	Douglas-fir	A	45.4	0.005
19	Abies grandis	grand fir	A	10.7	0.143
20	Rubus discolor	Himalayan blackberry	C	70.4	0.001
21	Arbutus menziesii	Madrone	A	9	0.587
22	Fraxinus latifolia	Oregon ash	В	3.4	0.762
23	Cornus nuttallii	Pacific dogwood	C	15.4	0.021
24	Taxus brevifolia	Pacific yew	В	5.1	0.579
25	Toxicodendron diversilobum	poison oak	В	13.8	0.119
26	Alnus rubra	red alder	В	4.7	0.662
27	Salix laevigata	red willow	C	7.7	0.139
28	Rubus spectabilis	salmon berry	В	5.3	0.498
29	Salix sessilifolia	sandbar willow	В	2.6	1
30	Salix sitchensis	Sitka willow	C	7.7	0.15
31	Lithocarpus densiflorus	Tanoak	A	63.2	0.001
32	Heteromeles arbutifolia	Toyon	C	5.1	0.447
33	Quercus lobata	valley oak	В	10.5	0.103
34	Myrica californica	wax-myrtle	A	5.4	0.311
35	Rhododendron occidentale	western azalea	A	15.4	0.038
36	Plantanus racemosa	western sycamore	C	7.7	0.135
37	Alnus rhombifolia	white alder	C	51	0.001
38	Salix alba	white willow	C	23.1	0.006

^{*} proportion of randomized trials with indicator value equal to or exceeding the observed indicator value (Dufrene and Legendre 1997).

P = (1 + number of runs) >= observed)/(1 + number of randomized runs)

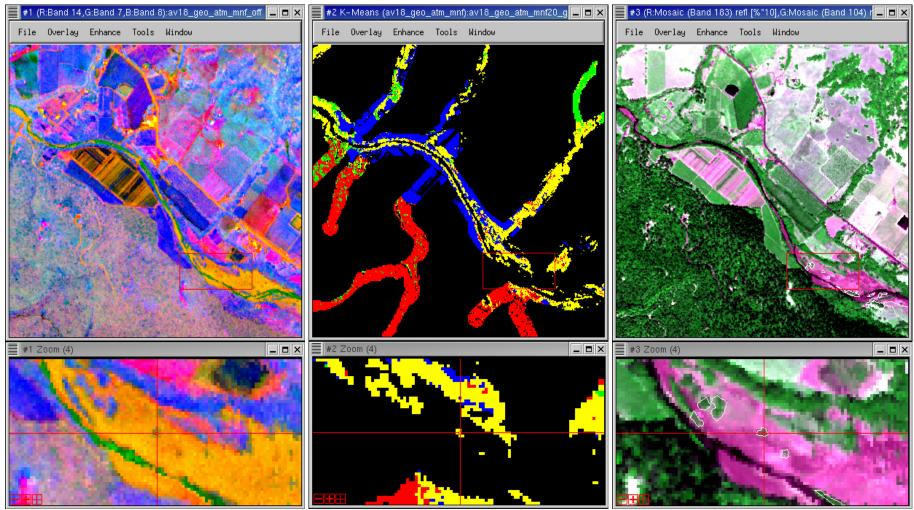


Figure 4.1. Navarro River AVIRIS Image Minimum Noise Fraction Transform (Planes 14, 7, 8).

Figure 4.2. Navarro River AVIRIS Riparian Vegetation Classification (Class A in Red, Class B in Green, Class C in Yellow, and Cultivated Crops in Blue).

Figure 4.3. Navarro River AVIRIS Image of Hendy Woods State Park (Bands 183, 104, 195) with GPS Verification Overlay (White Polygons) targeting Class C pixels

Comparatively, California bay laurel (*Umbellularia californica*) was the only Indicator Species to not represent more than 50% of its associated Class pixels; it represented only 28.84% of Class B. Without additional fieldwork, it is difficult to determine if the SAM performed poorly for bay laurel or if the incorporation of other diagnostic species, such as big leaf maple (*Acer macrophyllum*), would be more appropriate for this class. Class B must also be considered a "mixed hardwood" community and, as such, would naturally have a great number of possible species in its class. Regardless, each Indicator Species had the predominate percent of its pixels within its associated K-Means class. Coastal redwood (*Sequoia sp.*) performed the best at 70.72% of its SAM pixels in Class A. Furthermore, it is also apparent that traditional riparian vegetation, as represented by willow (*Salix spp.*) for example, are true to their ecological form in terms of being generally interspersed within other vegetation communities; this is evidenced by each of the three K-Means riparian classes having more than 20% of its pixels classified as arroyo willow (*S. lasiolepis*) by SAM. Arroyo willow represented 53.43% of Class C. In the case of true riparian vegetation, additional diagnostic species will need to be incorporated into future SAM classification efforts if the identification of species will be used as a surrogate for classifying vegetation communities.

These results are for a limited portion of the watershed and could change with the incorporation of other flightlines and other field plots. Some considerations for addressing possible error include: 1) the mixed composition of vegetation communities are difficult to separate spectrally by species; 2) the "ribbon" forest nature of riparian vegetation can be overwhelmed by upland species; and 3) canopy structure, especially with 80–100 m tall coastal redwood trees, can obscure other vegetation features. The preliminary results of this effort indicate that hybrid methods of feature extraction work best in this varied landscape of topography, climate, and vegetation communities. Additional research will be focused on assessing other discriminatory methods for feature extraction within the riparian zone and other feature types. However, assessing the distribution and composition of riparian vegetation at a watershed scale is essential to protecting salmonid habitat and guiding restoration efforts. The methods outlined here, as they are improved, will aid land use managers in their ability to inventory, restore, and monitor riparian ecosystems. This is particularly true for north, coastal California watersheds where recent policy determinations under the federal Clean Water Act and Endangered Species Act require regulatory agencies to assess ecosystem integrity in a comprehensive and timely manner.

Acknowledgements:

We would like to thank the following entities and individuals for the support in this project: Lisa Levien, Chris Keithley, Bruce Gwynne, David Leland, Zhi-Wei Lu, George Scheer, Susan Ustin, Eric Lehmer, Derek Masaki, Bob Brewer, Anni Schairer, the Information Center for the Environment, UC Davis Department of Environmental Science and Policy, the John Muir Institute of the Environment, the Center for Spatial Technologies and Remote Sensing, the Center for Image Processing and Integrated Computing, and the University of California. This work was partially supported by funding from the North Coast Regional Water Quality Control Board, California Department of Transportation, California Department of Forestry and Fire Protection, and United States Department of Agriculture – Forest Service.

Citations:

- Boardman, J.W. and Kruse, F.A., 1994. Automated Spectral Analysis: A Geological Example Using AVIRIS Data, North Grapevine Mountain, Nevada: in *Proceedings, ERIM Tenth Thematic Conference on Geologic Remote Sensing*, Research Institute of Michigan, Ann Arbor, MI, ppd. I-407 I-408.
- Boardman, J.W., Kruse, F.A and Green, R.O., 1995. Mapping Target Signatures Via Partial Unmixing of AVIRIS data: in Summaries, *Fifth JPL Airborne Earth Science Workshop*, JPL Publication 95-1, V. 1, ppd. 23-26.
- Dufrene, M. and P. Legendre. 1997. Species assemblages and indicator species: the need for a flexible asymmetrical approach. Ecological Monographs 67:345-366.
- Environmental Systems Research Institute, Inc. 2001. Version 8.1 Redlands, CA 92373-8100, USA.
- Environment for Visualizing Images (ENVI), Version 3.5. Research Systems, Inc., Boulder, CO, 2001.
- Hill, M.O. 1979. TWINSPAN--A FORTRAN program for arranging multivariate data in an ordered two-way table by classification of the individuals and attributes. Ithaca, NY: Ecology and Systematics, Cornell University.
- Jackson, R.D., 1983. Spectral Indices in *n*-Space. *Remote Sensing of the Environment*, 13, ppd. 409-421.

- Kruse, F.A., Lefkoff, A.B., Boardman, J.B., Heidebrecht, K.B. Shapiro, A.T., Barloon, P.J. and Goetz, A.F.H., 1993.
- The Spectral Image Processing System (SIPS) Interactive Visualization and Analysis of Imaging Spectrometer

 Data: Remote Sensing of the Environment, Special Issue on AVIRIS, May-June 1993, V. 44, p. 145-163
- McCune, B. and M.J. Mefford. 1999. Multivariate Analysis of Ecological Data Version 4.14. MjM Software, Gleneden Beach, Oregon, USA.
- Richards, J.A. & Jia, X., 1999. *Remote Sensing Digital Image Analysis: An Introduction*. Berlin, Germany, Springer-Verlag.
- Richter, R. 2000, Atmospheric / Topographic Correction for Wide FOV Airborne Imagery: Model ATCOR4, DLR-German Aerospace Center, Wessling, Germany.
- Roberts, D. A., M. Gardner, R. Church, S. Ustin, G. Scheer and R. O. Green. 1998. Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models, *Remote Sensing of Environment*, Volume 65(3) ppd. 267-279
- Schläpfer, D. 2000, Parametric Geocoding User Guide, Version 1.3, Remote Sensing Laboratories, University of Zurich, Zurich, Switzerland.
- van Tongeren, O.F.R. 1995. Cluster analysis in *Data Analysis in Community and Landscape Ecology*. R.H.G. Jongman, C.J.F. ter Braak, and O.F.R. van Tongeren, editors. Pudoc, Wageningen, The Netherlands.

Appendix I

Field Plot Samples

 $\frac{122222223333333344444455566666667778}{9012346812345678235679189123456913673578901234567857909014856707805901245671234602342488}$

The call		Species		1	
7 Rha cal	3		-11-2-112113-1-121-11-	222-4113113332233-121221-3311212-121	1
Solution Control Con	4	Que_kel		-2111	
9 Tor_cal 11 Que wiz 2 Que agr 12 Que agr 13 Seq sem 14 Cea inc 16 Arc man 17 Page men 18 Page men 19 Abi gra 18 Tax bre 26 Aln rub 27 Rub spe 28 Rub spe 29 Sal ses 31 Lit den 31 Squ lob 31 Lit den 31 Squ lob 32 Rub cea inc 33 Que lob 34 Ryr cal 35 Rho occ 37 Ace mac 38 Rub men 39 Tor_cal 30 Que lob 31 Squ lob 32 Rub men 34 Tax bre 35 Rho occ 36 Ro occ 37 Ro occ 38 Rub men 39 Ro occ 30 Ro occ 30 Ro occ 30 Ro occ 31 Ro occ 31 Ro occ 31 Ro occ 32 Ro occ 33 Ro occ 34 Ro occ 35 Ro occ 36 Ro occ 37 Ro occ 38 Ro occ 39 Ro occ 30 Ro occ 30 Ro occ 30 Ro occ 31 Ro occ 31 Ro occ 31 Ro occ 32 Ro occ 34 Ro occ 35 Ro occ 36 Ro occ 37 Ro occ 38 Ro occ 38 Ro occ 39 Ro occ 30 Ro occ 30 Ro occ 31 Ro occ 31 Ro occ 31 Ro occ 32 Ro occ 34 Ro occ 35 Ro occ 36 Ro occ 37 Ro occ 38 Ro occ 38 Ro occ 39 Ro occ 30 Ro occ 30 Ro occ 30 Ro occ 31 Ro occ 31 Ro occ 31 Ro occ 31 Ro occ 32 Ro occ 34 Ro occ 35 Ro occ 36 Ro occ 37 Ro occ 38 Ro occ 38 Ro occ 39 Ro occ 30 Ro occ 31 Ro occ 30 Ro occ 31 Ro occ 31 Ro occ 32 Ro occ 33 Ro occ 34 Ro occ 35 Ro occ 36 Ro occ 37 Ro occ 37 Ro occ 38 Ro occ 37 Ro occ 38 Ro occ 30 Ro occ	7	Rha cal	111-1		
11 Que wiz	8	Cor cor	-111-	11	
1	9	Tor cal	111	112	
12 Que agr	11	Que wiz		1-212	
14 Cea inc Arc_man 16 Arc_man -2-432-334342111-11-11131-22-221-111-12-21212-12-111-111	12	_	121	1-32111	
14 Cea inc Arc_man 16 Arc_man -2-432-334342111-11-11131-22-221-11-12-21212-12-111-111	13	Seq sem	43143332432214123343433-2-2-332423314	3	1
16 Arc_man -2-432-334342111-11-11131-22-221-11-12-21212-12-111-111	14	Cea inc			
19 Abi_gra 3-4-2 1	16	_		 1	
24 Tax bre	18	Pse men	-2-4323343421111111131-22221-	-11-12-2121212-111111331-111	1
24 Tax_bre	19	Abi qra	3-421	 1	
26 Aln_rub	24		1	11	
Sal Ses	26	Aln rub			
31 Lit_den -31332-1223422233-1313242121-2221-1-121-12111-1-1-2-2-111	28	Rub spe		11	
33 Que_lob	29	Sal ses		3	
33 Que_lob	31	Lit den	-313321223422233-1313242121-2221	1-121-211-2111112-2-11	
35 Rho occ	33	Oue lob			
35 Rho_occ	34	~ _ Mvr cal	-12		
2 Ace_mac		<u> </u>		1	
10 Vit_cal	2	_			11
21 Arb_men	10	_	1	11111	1
5 Rub_urs 111 121	21	Arb men	11-11-11	111111	1-
25 Tox_div	22	Fra lat		24	1
25 Tox_div	5	Rub urs	1111	121111	1-1121
1 Sal_las	25	-		11111	11
6 Aes_cal 15 Sal_hoo 17 Bac_pil 20 Rub_dis 21 Cor_nut 27 Sal_lae 30 Sal_sit 32 Het_arb 36 Pla_rac 37 Aln_rho 38 Sal_alb 38 Sal_alb 39 Sal_alb 30 Sal_alb 30 Sal_alb 31 Sal_alb 32 Sal_alb 33 Sal_alb 34 Sal_alb 35 Sal_alb 36 Sal_alb 37 Sal_alb 38 Sal_alb		_	1111	1111	 21221112-
15 Sal_hoo	6	_		 11	-1
17 Bac_pil	15		11		2
20 Rub_dis -1		_	1-		12-
23 Cor_nut			11	111	1321-213311
27 Sal_lae					11
30 Sal_sit		_			_
32 Het_arb11		_			
36 Pla_rac		_	111		1_
37 Aln_rho -113211111111112211131-413111- 38 Sal_alb22221221		_	=	_	
38 Sal_alb221					 131-413111-
		-			
TO CLASS A TO CLASS B TO CLASS CO. I	20	541_415	Class A	Class B	Class C